Using Multiple Membership Multilevel Models to Examine Multilevel Networks in Networked Organizations

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Abstract

As the network structures of work and community have grown more complex, multilevel networks have emerged as the main structural feature in organizational settings. Stressing the importance of the affiliation ties of the meso-level network, we propose a conceptualization of multilevel networks within networked organizations. To examine such networks, researchers have used both hierarchical linear models (HLMs), and exponential random graph models (ERGMs) and both show strengths and weaknesses. HLMs have focused on the effects of group characteristics on individual level nodes, and assumed that each node is affiliated with only one group. Thus they are unable to analyze the complexity of the cross-cutting ties in multievel network data from networked organizations. ERGMs, on the other hand, have been used for analyzing such networks and are able to show if the presence of certain ties shapes the development of others. However, these models assume that networks are self-organizing systems of endogenous ties and, as a result, exogenous factors are excluded from them. In this paper, we propose a new method of multiple membership multilevel models that reveal the complexity of the network at the meso-level, i.e., multiple ties between one individual-level node and multiple group-level nodes. To accomplish this we offer an examination of the Canadian research organization, GRAND NCE (Graphics, Animation, New Media and Design Network of Centers of Excellence).

Key words

Multilevel networks, multilevel multiple membership models.

1. Introduction

As work and community become structured as complex social networks, we need to develop methods to understand them better. Since the 1990s, scholars in organizational studies have noticed the emergence of the network form of organization, alongside the more traditional market and hierarchical forms of organization (Larson and Starr, 1993; Powell, 1990). The networked form of organization, also called a networked organization, is distinguished from the hierarchical form by the reciprocal and lateral patterns of communication that emerge within the organization when members possess particular knowledge that is not limited to specific tasks, but applicable to a wide range of activities within the organization (Powell, 1990). In traditional hierarchical organizations, people form a set of relatively simple ties, often in single-dimensions and within strict work unit boundaries, such as within particular departments. During the shift to a networked organization, people networks transform to become multidimensional and multilayered, as relationships spanning the fuzzy boundaries between new forms of working units, such as teams, take root. (Krebs, 2007; Larson and Starr, 1993; Rainie and Wellman, 2012).

Thanks to the shift to an information economy and the diffusion of information and communication technologies (ICTs), the number of networked organizations is growing (Castells, 1996; Rainie and Wellman, 2012). This trend is reported in the Pew Internet's Networked Worker Survey (2008), which found that 64% of American workers participate in at least one team while 41% belong to multiple. Having memberships in multiple teams simultaneously is a unique characteristic of networked organizations. Research has suggested that networked organizations have several advantages in allocating people and resources to projects while, at the same time, are able to foster autonomy, flexibility, and decentralized control (Rainie and Wellman, 2012).

In networked organizations, networks are developed both within each level of the organization and across them. Although the networked form of organization is discussed in stark contrast to traditional bureaucratic organizations, they do not necessarily exhibit a flat and decentralized structure (Powell, 1990). Research has elaborated that a mixed hierarchical structure and flat networks exist in networked organizations (Ahuja and Carley, 1999; Rhoten, 2003; Shrum et al., 2007). The coexistence of both means that networks among members are developed in various domains, such as friendship networks, communication networks, and advice networks, while higher-level divisions, such as teams or groups, still constrain workers' activities and performance to some degree. People's networks are partly embedded in, and shaped by, their work units at a higher level.

To examine how the complex multilevel social networks of networked organizations shape the individual networks within them, we introduce multilevel multiple membership models in this study. We define multilevel networks in networked organizations as networks that consist of multiple sets of nodes at multiple levels of the organization, where individual level nodes form at least one type of tie among each other, and each node is affiliated with one or more higher level units (Figure 1.2).

Multilevel networks have drawn the attention of many social network analysts who have come to use two distinctive methods in their examination, Hierarchical Linear Models (HLMs) and Exponential Random Graph Models (ERGMs), each of which have their own strengths and weaknesses. HLMs largely ignore the interactions among group members at the micro-level (Wang et al., 2013), while ERGMs provide a more complex representation of the interdependence among groups and their members. Additionally, ERGMs assume that all nodes, regardless of their hierarchical dimension, play an equal role within the network, while HLMs assume that individual-level nodes belong to one, and only one, group-level unit. Unfortunately, these models can only be used for certain types of organizational structures, but not for the multilevel networks found in networked organizations.

In this study, we present multiple membership multilevel models to elaborate the mechanisms of networks at different levels of a networked organization. As an example, we will examine the GRAND Network of Centres of Excellence, a large, national research organization. Focusing on its formal affiliation network at the meso-level, and the actual multidisciplinary communication networks at the individual level, we aim to elaborate how the characteristics of group-level units affect networks at the individual level through the meso-level network. The proposed models are analyzed using Stata statistical software.

2. Multilevel networks in networked organizations

Social network analysis in general presents complex representations of the interdependence among nodes. The complexity, to a large degree, emerges from network structures where nodes are connected by various types of ties at various levels of the networks hierarchy. Since the 1960s, social network analysts have studied multilevel networks or two-mode networks, which refer to networks that contain two sets of nodes, one of which has ties to another set (Wasserman and Faust, 1994). In the past few years, researchers have shown great interest in multilevel networks and used various terms, such as multinetworks, multiplex networks, and multilevel networks, to describe such complex structures (Kivelä et al., 2013). In this section, we review empirical works on the topic and propose a specific definition of multilevel networks in networked organizations that we will use in this article.

Multilevel network usually refers to networks consisting of nodes and ties in two levels – the individual level, or the micro-level, and the group level, or the macro-level. Acknowledging these two levels in social networks, Simmel (1955) pointed out that each tie between two distinct groups forms an "intersection" of the groups' membership by way of a set of individuals, this relationship is referred to as dualism. Although Simmel mainly discussed how groups are connected by common members, it is notable that the cross-level relationships, i.e. the persons' membership in the groups at the meso-level, are the premise of dualism.

Nevertheless, we argue that meso-level networks, as opposed to networks at the individual or group level, are the primary structure in multilevel networks. This is because networks are only considered multilevel when it contains cross-cutting ties. Breiger (1974) produced the broadest configuration of a multilevel network – it only contains a meso-level network (Figure 1.1). Based on Simmel's (1955) concept of dualism, Breiger (1974) further developed the idea in his work "*The Duality of Persons and Groups*". Here he views networks as consisting of both sets of individuals, and sets of groups, thus affiliating them through networks composed of two levels. In such networks, "the value of a tie between any two individuals is defined as the number of groups of which they both are members. The value of a tie between any two groups is defined conversely as the number of persons who belong to both" (Breiger, 1974). Although dualism is a framework including nodes at two levels, no direct relationships are required among nodes within each level. However, when individuals' membership or affiliation with nodes at the group level represents a form of social tie, such as being a member of a team or participating in a research project, the membership is also a type of level spanning relationship which forms the meso-level network structure (Wang et al., 2013). The approach of dualism is also advanced by Fararo and Doreian (1984) in tripartite networks. In such networks, people are nested in groups, and groups within organizations, thus the network structure exhibits three levels.

Building on Breiger's dualism, Wasserman and Faust (1994) described a type of multilevel network known as "affiliation networks". An affiliation network consists of one set of nodes at the individual level, and another set of nodes at the group level which serve to affiliate them. The ties among individuals are not required, but the people must be affiliated with one or more groups connecting them at a higher level. Therefore, the primary component of affiliation networks is also the meso-level network. The concept of affiliation networks contributes to social network analysis as it sheds light on the bridging function of group level nodes for individual level nodes. It suggests that networks at the individual level are formed because of their joint affiliation with nodes at the group level.

Although meso-level networks are an indispensable part of the conceptualization of multilevel networks, they have yet to be fully examined in empirical works. Most studies on multilevel networks have underestimated the complexity of their structures at the meso-level. They also tend to examine networks at the individual level as nested within a higher level node, thus assuming that there is no overlap between groups as each individual level node is connected to only one group level node (de Miguel Luken and Tranmer, 2010; Snijders et al., 1995; van Duijn et al., 1999; Wellman and Frank, 2001).

Other studies have shed light on meso-level networks by examining networks at only a single level, such as the individual or group level (Figure 1.2). For example, Hedström et al. (2000) identified meso-level networks by investigating the network structure between Sweden's administrative districts. Here they reconstituted ties between administrative districts as nodes at the group level, and ties between individuals living within various districts as ties on the individual level. They found that information flows over long distances at the meso-level, such as across the country, were substantially faster than information flows at the individual level.

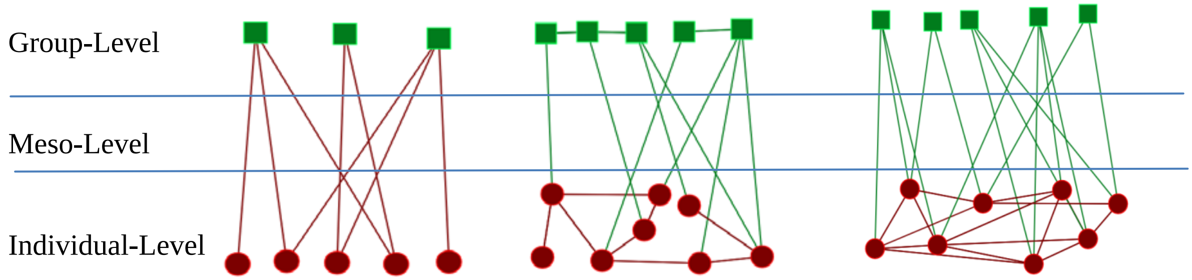

Fig. 1. 1. Two-mode network Fig. 1.2. A multilevel network* Fig.1.3. A networked organization

*Fig. 1.2. is adapted from Wang et al. 2013. Exponential random graph models for multilevel networks. Social Networks 35, 96-115, p.97.

Building upon the approach of reconstituting meso-level networks developed by Hedström et al. (2000), Lazega et al. (2008) analyzed multilevel networks among a group of elite cancer researchers and their laboratories in France. The authors used the method of structural linked design to examine how networks among laboratories and the advice giving networks among researchers were connected. To do this they created two categories for network members, central and peripheral researchers, or big and small fish. They also created central and peripheral categories for laboratories, or big and small ponds. Combing the categories from the individual and the group level, they identified four categories of ties at the meso-level: the big fish in a big pond, the little fish in a big pond, the big fish in a little pond, and the little fish in a little pond. Each of these meso-level categories was found to use different strategies, namely individualist strategy, independent strategy, collectivist strategy, and fusional strategy, to reach the highest level of performance. Extending this method, Bellotti (2012) conducted a similar study of Italian researchers and their funded projects, finding that better connected researchers tended to work in larger departments.

Wang et al. (2013) also employed the dataset of the French cancer researchers and their laboratories (Lazega et al., 2008) to propose an innovative method to apply Exponential Random Graph Models to help understand the emergence of networks in multilevel networks. By including the meso-level structure as one of the configurations in multilevel networks, the authors concluded that “even simple cross-level effects can create highly structured within-level networks” (Wang et al., 2013).

These studies have made important contributions to multilevel network analysis because they identify ties at the meso-level, highlight the effects of meso-level network structure, and reveal how individual level networks and group level networks are connected at the meso-level. However, it is difficult to adopt the research methods used in these studies to investigate networked organizations. This is because networked organizations are characterized by a more complicated meso-level structure – individuals are potentially affiliated not only by one, but by multiple groups.

In this study, we propose a more specific configuration of multilevel networks within networked organizations (Figure 1.3). We suggest that the definition of multilevel networks in networked organizations should include three fundamental components: two sets of nodes composed of the individuals (a) and groups (b), networks within the individual level (A), and each individual's membership in one or more than one group (x) which in turn form into the affiliation network or the meso-level network. The ties among groups are not required because groups are connected through their common members. We stress that the meso-level network (X) is more static when compared to the networks at the individual level as it is constrained by characteristics of the groups.

3. Exponential random graph models for two-level networks

Exponential random graph models (ERGMs) have become a popular method to analyze multiple level networks (Wang et al., 2013). Different from the conventional social network analysis which only studies the observed networks, ERGMs aim to unveil the mechanisms driving the formation of observed networks. Using the set of fixed nodes in the observed networks, ERGMs generate the probable distribution of configurations randomly, or based on certain network regularities such as reciprocity. By comparing the simulated configurations, and the configuration identified in the observed network, ERGMs are able to assist researchers in deducing the initial mechanism that lead to the formation of the observed network. ERGMs assume that social networks are the results of regularities, interdependence, and randomness. They assume that social ties are formed based on the presence, or absence, of other ties within a fixed node set. In other words, each tie is regarded as a random variable, whose connection to any other is contingent on other ties within the same network, or micro-level attributes (Robins et al., 2007).

A recent contribution in multilevel network analysis using ERGMs is that of Wang and his colleagues (2013). Addressing ERGMs' weakness that cross level structures are often ignored, they proposed a model taking both configurations within each level, and those across levels into account:

$$\Pr(\mathrm{A}=\mathrm{a},\quad \mathrm{X}=\mathrm{x},\quad \mathrm{B}=\mathrm{b}) = \left(\frac{1}{k(\theta)}\right)\exp\sum_{Q}\{\theta_Q z_Q(\mathrm{a})+\theta_Q z_Q(\mathrm{x})+\theta_Q z_Q(b)+\theta_Q z_Q(\mathrm{a},\mathrm{x})+\theta_Q z_Q(\mathrm{b},\mathrm{x}) + \theta_Q z_Q(\mathrm{a},\mathrm{x},\mathrm{b})\}$$

Where:

- *A* is a network realization at the macro-level, and *a* is the observed network at the same level; *X* is a network realization at the meso-level, and *x* is the observed network; *B* is a network realization at the micro-level, and *b* is the observed network.

- The summation of all configurations is Q.
- θ_Q is the parameter corresponding to configuration Q.
- $z_Q(a)$ and $z_Q(b)$ are the network statistics corresponding to within level network configuration Q.
- $z_Q(x)$ are the network statistics for the cross level effects in the meso-level configuration Q.
- $z_Q(a, x)$ and $z_Q(b, x)$ are network statistics for the configurations involving ties from either the micro- or macro-level network and the meso-level network, and represent the interactions between the two networks.
- $z_Q(a, x, b)$ are statistics for the configurations involving ties from all three networks.

Applying this model to the analysis of the networks among French cancer researchers and their laboratories, Wang and his colleagues (2013) identified each of the cross level parameters, such as affiliation based closure or homophily by shared affiliations, and revealed the interdependence between networks across all of their various levels (i.e., the advice network at the micro-level is likely to be concurrent with the collaborative networks at the macro-level). Furthermore, they also pointed out that the interdependence is less likely to occur when reciprocity occurs in either the macro- or micro-level.

ERGMs for two-level networks enable social network analysts to not only uncover the complicated features of multilevel networks, but also explain the formation of ties by looking at cross-level interactions. However, such models have some limitations. First, ERGMs assume that units, at both the macro- and the micro-level, are playing equivalent roles for leading to the emergence of ties. This assumption ignores the constraining effects of the macro-level units on the ties at the micro-level and focuses only on the interdependence between networks. In their study examining the development of friendship ties in voluntary groups, McPherson and Smith-Lovin (1987) addressed that friendship ties are more likely to emerge in homogenous groups than heterogeneous groups. In other words, the composition of macro-level units affects the development of ties at the micro-level. Although ERGMs for two-level networks allow researchers to elaborate on the complexity of network structures and their cross-level interactions, they ignore the fact that the micro-level ties are nested within the macro-level units, thus providing an incomplete explanation about the formation of ties at the micro-level.

Second, ERGMs assume that networks are self-organizing systems of ties (Robins et al., 2007). The assumption is that ties come into being in ways that are shaped by the presence or absence of other ties (Lusher et al., 2013). Homophily, reciprocity, or transitivity are frequently examined social processes that generate ties in local networks (Contractor et al., 2006; Su et al., 2010; Wang et al., 2013). In networked organizations, members' networks are more likely to be designed rather than emerging from a natural development process. In these cases, network theories such as reciprocity or homophily may fail to provide reasonable explanations for network structures. In other words, networks of design may present a different structure than others, not explained by current network theories.

Finally, ERGMs treat ties as endogenous and understood, meaning that various properties of the network influence the probability of the presence or absence of ties (Contractor et al., 2006). As a result, the strengths of such models are revealed in answering research questions about the interdependence of the networks within or across levels. For instance, how does network A develop from network B among the same group of people? What causes the cliques in network A, homophily or reciprocity? These questions represent a binary view of ties as being either present or absent and, as a result, questions beyond such binary considerations cannot be explored with ERGMs. For instance, how does the combination of macro-level unit shape homophily within the micro-level network? How does the size of the macro-level unit affect the centralization of the micro-level network? These questions often require that exogenous factors, or properties outside the network such as the attributes of network members, be taken into consideration. In other words, ERGMs are not able to aid in understanding either how, and the extent to which, network characteristics and properties at the micro-level, are shaped by the macro-level units in which they are embedded.

4. Multilevel models

Social network analysts also use hierarchical linear models (HLMs) to investigate multilevel networks (Snijders 2003; Snijders and Bosker 2012). Generally, HLMs are used to both represent and estimate the effects of larger social units at a higher level, such as groups, neighborhoods, and organizations, on individuals themselves or other, lower level, units. In HLMs, the lower-level is often called the individual level and the higher-level the group level. The underlying assumption is that the social structures, policies, demographic compositions, and social climates that people are embedded in, directly affect individual behavior. In other words, a hierarchy determines the structure of units at both the individual level and the group level. HLMs are often used to explore questions related to between-group variability, and the effects of group level characteristics on outcomes at the individual level. The between-group variability, therefore, is apportioned across both levels.

Suppose we have J groups, and there are a different number of I individuals in each group. We are interested in the effect of some X on Y, where the independent variable X is an individual-level factor. When studying the effect of X on Y separately in each group, we produce J different regression and combine the results. The independent variable at the individual level is denoted by X_{ij}, where the i and j subscripts on X show that its values vary across individuals within a group. The simplest multilevel model, also called a random intercept model, assumes that the effect of X on Y is the same for each group. This model, with a single independent variable at the individual level, can be expressed as

$$Y_{ij} = \beta_0 + \beta_1 X_{ij} + u_j + e_{ij}$$

Where: Y_{tj} is the dependent variable; β_0 is the intercept and β_1 is the slope; u_j is a random effect at group level, and e_{tj} is a random effect at the individual level. Therefore, the over-all relationship between *Y* and *X* is represented by a straight line with β_0 and β_1. However, the intercept for a certain group *j* is β_0+u_j, and the intercept of that group *j* is higher or lower than the overall intercept β_0 by an amount u_j. Therefore, the variance of Y_{tj} is decomposed into the variances at the group and individual levels.

The random intercept model assumes that the slope β_1 is fixed across groups. This constraint is relaxed when the relationship between *X* and *Y* varies randomly across groups. When the slope associated with the individual-level, independent variable is group dependent, we use a random slope model:

$$Y_{tj} = \beta_0 + \beta_1 X_{tj} + u_{0j} + u_{1j} X_{tj} + e_{tj}$$

Which can also be written as:

$$Y_{tj} = \beta_{0j} + \beta_{1j} X_{tj} + e_{tj}$$
$$\beta_{0j} = \beta_0 + u_{0j}$$
$$\beta_{1j} = \beta_1 + u_{1j}$$

Where: $\beta_0 + u_{0j}$ defines the intercept, and $\beta_1 + u_{1j}$ defines the slope. In other words, the slope of the average regression line is β_1, and the slope of the line of a certain group is $\beta_1 + u_{1j}$.

HLMs can also include group-level variables to examine contextual effects. In this case, the individual-level variable is denoted as X_{1tj}, and the group-level variable is denoted as X_{2j}. The model can be expressed as:

$$Y_{tj} = \beta_0 + \beta_1 X_{1tj} + \beta_2 X_{2j} + u_j + e_{tj}$$

Where: $\beta_0 + u_j + e_{tj}$ is the intercept of the regression line of a certain group *j*, and both β_1 and β_2 define the slope. The group-level variable and the individual-level variable jointly account for the variance in Y_{tj}.

These models are increasingly used by social network analysts (Schweinberger and Snijders, 2003; Snijders et al., 1995; Snijders and Bosker, 2012) who assume that the characteristics of group-level units can directly affect the behavior of individuals embedded within them. HLMs share a similar data structure with social network theories that propose the multilevel nature of social networks in that both reveal lower-level units as being nested in higher-level ones. For instance, Wellman and Frank (2000) used HLMs to examine how networks facilitate supportive ties. Viewing supportive ties as the dependent variable at the individual level, and network composition as independent variable at the group level, they found that parents and children are more supportive in networks with high percentages of parents and children. Nevertheless, some social network analysts criticized that HLMs mainly focus on the effects of group characteristics on the individual level variables rather than the relationships or networks within either individual or group level (Wang et al., 2013).

In addition, HLMs assume that each individual is affiliated with only one group, and though this may be legitimate for many frequently used group-level units, such as schools and neighborhoods, the result is that HLMs are not applicable for cases with complicated meso-level ties. Here individuals may have multiple memberships in various groups, suggesting a non-hierarchical network structure. Thus, HLMs are unable to analyze multilevel network data in networked organizations.

5. Multiple membership multilevel models

Based on HLMs, multiple membership multilevel models take the complexity in meso-level networks into consideration (Hill and Goldstein, 1998; Leckie, 2013; Rasbash and Brown, 2001). As stated above, people in a networked organization tend to work in multiple units at the same time. For instance, researchers in a large research network may work on several different research projects. The meso-level network in this setting is more complicated than that in a regular bureaucratic organization because each node at the micro-level may be connected to more than one node at the macro-level, and the number of ties each micro-level node has with the macro-level nodes varies. In other words, researcher A may be involved in five projects while researcher B engages in only one.

Furthermore, it is important to understand that the degree to which an individual belongs to each group varies across the groups. For instance our data shows that Researcher 33, involved in five out of six projects in a research organization, spent 50% of her time on Project 1, and 20%, 20%, 5%, and 5% on Project 2, 3, 5, and 6 respectively. The degree of each person's involvement in all groups can be viewed as the value of tie strength at the meso-level.

To consider the complexity of the meso-level structure, we use the multiple membership multilevel models developed by Hill and Goldstein (1998). They assigned a proportional weight according to each individual's memberships within each unit, and within the group as a whole, summing to 1. In other words, the strength of ties at the meso-level network are transformed into proportions so that the total of each nodes strength of ties at the micro-level added up to 1.

In a networked organization, the membership weights are denoted by w_{ij} for individual *i* in group *j*, adding up to 1 for every member in the organization.

$$\sum_{j=1}^{J} w_{ij} = 1$$

Note that some individuals are only involved in one group, so there is only one meso-level tie for them and the strength of this tie is 1. To indicate the missed ties with other units at the group level, we use 0 to express the strength of ties. For example, the equation for the Researcher 33 in the example used above is listed as:

$$Y_{33} = \beta_0 + w_{33,1}u_1 + w_{33,2}u_2 + w_{33,2}u_3 + w_{33,4}u_4 + w_{33,5}u_5 + w_{33,6}u_6 + e_{33}$$
$$= \beta_0 + 0.5u_1 + 0.2u_2 + 0.2u_3 + 0.05u_5 + 0.05u_6 + e_{33}$$

This hierarchical, crossed, and multiple membership structure is thus modelled as:

$$Y_{ij} = \beta_0 + \sum_{j \in J} w_{ij}\, u_j + e_{ij}$$
$$u_j \sim N(0, \sigma_u^2)$$
$$e_{ij} \sim N(0, \sigma_e^2)$$

The subscript *j* denotes that a micro-level node does not necessarily connect to one unique macro-level node. Therefore, the macro-level random effect u_j is weighted by w_{ij}. For an individual *i*, who is not connected with group *j,* it has $w_{ij} = 0$, so they do not contribute to the meso-level network.

If there are independent variables at the micro- and/or macro-level, then the same kind of weighting is used for these variables (Leckie 2013). A model, where we include one micro-level independent variable and one macro-level independent variable is written as:

$$Y_{ij} = \beta_0 + \beta_1 X_{1ij} + \beta_2 \sum_{j \in J} w_{ij}\, X_{2j} + \sum_{j \in J} w_{ij}\, u_j + e_{ij}$$
$$u_j \sim N(0, \sigma_u^2)$$
$$e_{ij} \sim N(0, \sigma_e^2)$$

Where:

- In the fixed part of the model, $\sum_{j \in J} w_{ij}\, X_{2j}$ is the weighted sum of the macro-level independent variable with slope coefficient β_2.
- $\sum_{j \in J} w_{ij}\, u_j$ is the weighted sum of the random effects at the macro-level.
- And $\beta_0 + \sum_{j \in J} w_{ij}\, u_j + e_{ij}$ determines the intercept of each regression line.

6. Example of multiple membership multilevel models

6.1. A Networked Organization – GRAND

To serve and an example of multiple membership multilevel models, we studied the networked research organization GRAND NCE (Graphics, Animation and New Media Network of Centres of Excellence). It was formed at the start of 2010 to serve as a catalyst for research and innovation for new media and information technologies. As all NCEs, GRAND creates a flexible, networked organizational form, based less on formal ties, and more on permeable and boundary-spanning flows. It is a loosely connected network of academics, government and industry decision-makers and researchers, NGOs, and other stakeholders that are united by shared interests in studying new media and information technologies.

At the time of our study, GRAND was composed of 144 academics: 60 (41.7%) of them were project leaders holding the title of Network Investigators (NIs), while the remaining 84 (58.3%) were Collaborating Researchers (CRs). GRAND requires NIs, the primary researchers in projects, to be involved in at least two projects, and CRs to be involved in at least one. All members are expected to work in a networked fashion and are encouraged to collaborate actively across projects, thereby pooling resources and information. Half (52%) of the members participated in multiple projects, thus becoming bridges that built connections between the projects.

The composition of the GRAND network is diverse in terms of discipline. GRAND's researchers come from 26 institutions of higher education dispersed across seven Canadian provinces, and members have reported their fields of study in 39 different disciplines. Their disciplinary backgrounds range from Computer Science and Engineering, to Art and Design, from Information Science and Journalism, to the Social Sciences and Humanities. For the convenience of analysis and discussion, GRAND’s administration also groups these disciplines into broader categories. Among members, almost half (46.5%) are computer scientists, while others come from Information Science, Communication, and Management (13.9%), Media, Design, and Arts (14.6%), Social Sciences (7.6%), Humanities (2.8%), Engineering (5.6%), and other professions such as medicine and journalism (9%).

GRAND's projects are multidisciplinary. Apart from the requirement of multiple memberships in projects, GRAND also encourages multidisciplinary collaborations. Among the 34 projects in the network, only three are composed of members from the same discipline. By contrast, two-thirds of the projects involve three or four disciplines.

GRAND offers an interesting example for multiple membership multilevel models for two primary reasons: First, GRAND represents a networked form of research organization that is distinguished from the traditional organizational structure in research institutes. One of the goals of GRAND is to promote the development of cross-disciplinary networks among researchers, institutions, and spanning large geographical distances, as opposed to than maintaining a rigid hierarchical structure. The effort to develop networks aims to generate an open, flexible, and fluid environment for collaborators.

Second, within GRAND both the hierarchical structure and the network structure exist simultaneously. Its Board of Directors, International Scientific Advisory Committee, and

Research Management Committee serve to deal with administration at a higher level, which elucidate GRAND's hierarchical structure. Additionally, among GRAND researchers, NIs are distinguished from CRs and given separate, hierarchical functions. Also, GRAND members' practices are required to follow some regulations prescribed by its leadership, for instance, research projects must be multi-disciplinary and NIs have to participate at least two projects, although some flexibility is allowed. This means that the regulations from the top of the organization have circumscribed the practices and performance of each research project and its members.

The hierarchical structure in GRAND consists of three major levels: the organization level, the project level, and the individual level, which, compared to traditional bureaucracies, is a flatter structure. However, at each level horizontal network structures may be observed, revealing GRAND's networked structure. At the organization level, all members are funded by GRAND and have the same access to other members. At the project level, we can see that all projects are connected because each overlapping members who participate in other projects simultaneously. At the individual level, researchers have developed informal networks in various dimensions, such as communication networks, advice networks, and friendship networks.

In summary, GRAND is neither a bureaucratic hierarchy nor a flat network. Rather, it is a combination of both. Additionally, the multiple memberships of project members make the organizational structure of GRAND more complicated. Therefore, we consider GRAND a good example to use multilevel multiple membership models.

As stated earlier, the particular strengths of a multilevel multiple membership models lie in examining complicated organizational structures. It may assist in determining how the characteristics of the project level network shape networks at the individual level, and how membership in multiple projects affects researchers' activities in their networks on the whole. With this in mind, we ask two questions: how does disciplinary diversity in research projects affect diversity in researchers' communication networks? And, which communication network, i.e. the email network or the face-to-face network, are more affected by the disciplinary diversity of projects in which researchers are involved?

6.2. Data

To understand the mechanisms between networks at various levels, we use two datasets. One is a roster containing the demographic details of each GRAND member, including age, gender, and professional data, such as their discipline, affiliation, and membership in GRAND projects.

The second dataset is composed of social network data collected through an online survey conducted from September to November, 2010. All 144 of GRANDs members were invited to participate and 101 of them completed the survey (70%).

The online survey provided the respondents with a full list of GRAND members and asked them to identify with which members they collaborate, exchange help and advice, are friends, or would like to meet. In addition, the survey also asked about the communication channels through which the respondents interact with collaborators, such as phone, email, or face-to-face interaction. This approach, starting with a roster of members, allows us to capture the GRAND network in various domains, such as the email network and the work network.

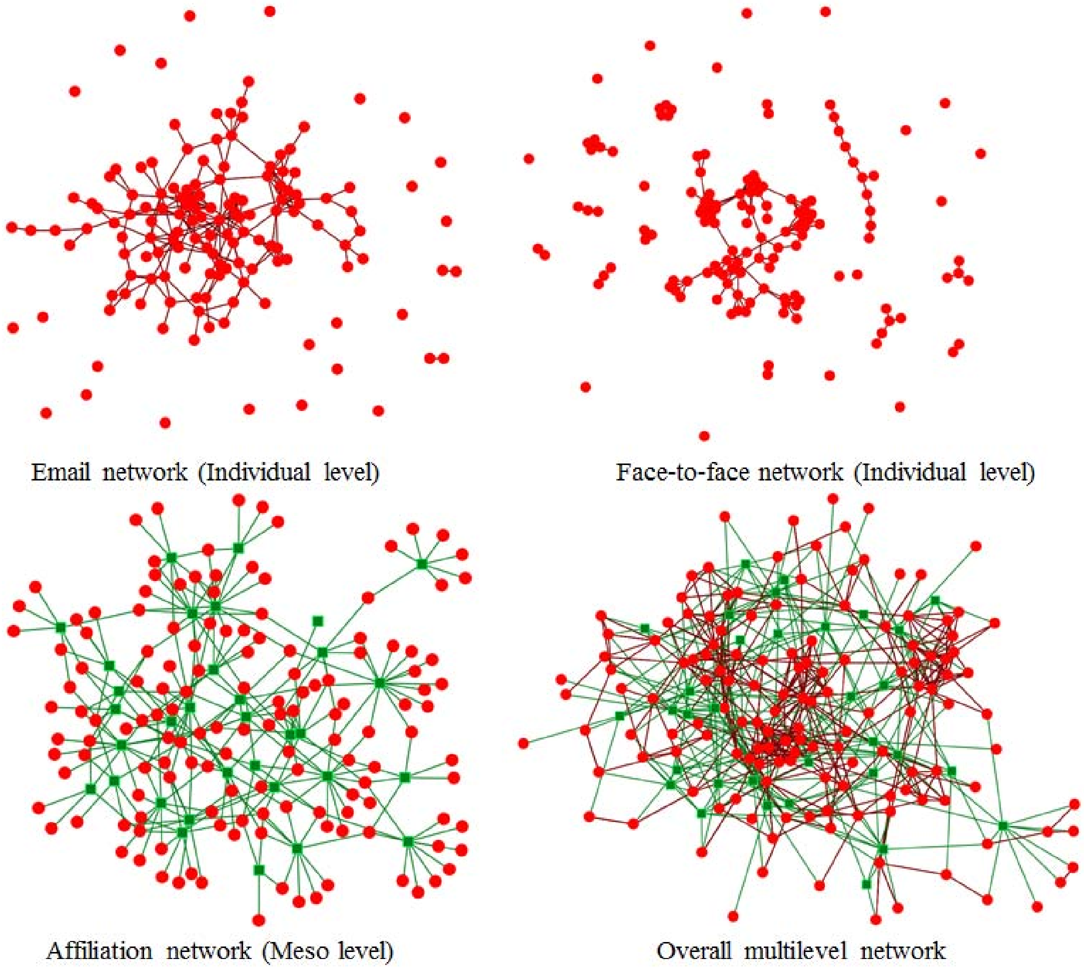

Fig. 2. The multilevel network among GRAND researchers

6.3. Variables and measures

The variables used in this example are grouped into one of four categories: (1) dependent variables (i.e., diversity in communication networks), (2) independent variables at the individual level (such as the roles of researchers in GRAND), (3) control variables at the individual level (such as a researchers gender), and (4) independent variable at the project level (i.e., disciplinary diversity).

6.3.1. Dependent variables

The variable of diversity in communication networks at the individual level captures the structure of GRANDs cross-disciplinary communications. In our survey data we found that email and face-to-face communication were the primary channels researchers made use of to engage in the collaborative process. As a result, our study focuses on these two major means of communication as dependent variables. Using this data, we created matrices of the email and face-to-face networks across GRAND.

We have used Blau's heterogeneity index (Blau, 1977) to measure the diversity in cross-disciplinary communication in the above networks so that we may identify the extent to which cross-disciplinary communication is practiced by each GRAND member. In other words, the heterogeneity in disciplines indicates the extent to which each researcher interacts with colleagues from differing disciplines. The heterogeneity index is calculated with the formula:

$$1-\sum p_i^2$$

Where p is the proportion of the group in the ith category. A higher index score indicates greater diversity among GRAND members along this particular dimension.

6.3.2. Independent variables at the individual level

Motivations for participating in multidisciplinary collaborations is a variable that elaborates upon how much a researcher is willing to engage in cross-disciplinary interaction. The survey data provide us with a matrix indicating who wants to meet whom in which discipline. By examining the want-to-know network, we use the heterogeneity index to understand whether researchers want to meet more collaborators from diverse disciplines or from the same background.

Academic status is measured along four dimensions: age, g-index, academic ranking, and the researcher's role in GRAND. The g-index is a tool for measuring scientific productivity based on publication records (Egghe, 2006), and is calculated based on the distribution of citations received by a given researcher's publications. "Given a set of articles ranked in decreasing order of the number of citations that they received, the g-index is the (unique) largest number such that the top g articles received (together) at least g^2 citations" (Egghe, 2006). It improves the h-index by giving more weight to highly-cited articles. The scores of each GRAND member are calculated based on the automated calculator supplied by the Web of Knowledge. Age and the g-index are both continuous variables.

The other two variables, academic ranking and role in GRAND, are both ordinal, being ranked by value. Academic ranking has three values: assistant professor, associate professor, and professor. Role in GRAND, on the other hand, has two values: network investigator (NI) and collaborating researcher (CR).

6.3.3. Control variables at the individual level

We use gender as a control variable given its importance in determining several characteristic. Gender has been found to influence people's structural positions in their networks (Moore, 1990), shape the entire structure of their networks (Erickson, 2004), and predict with whom they tend to be connected (McPherson et al., 2001).

We also control for the percentage of project members from the same department. Collaborators who can meet and discuss issues in person are able to communicate more efficiently compared to those at a distance. During the interviews with GRAND members, multiple respondents mentioned that collaborators in the same department tend to have face-to-face meetings more often and collaborate more closely. Therefore, we calculated the percentage of project members from the same department.

6.3.4. Independent variable at the project level

The multidisciplinary diversity in projects is calculated using the roster data. Rather than look at the actual networks developed among GRAND members, this variable elaborates the prescribed structure of each project – how multidisciplinary each is designed to be. We use the heterogeneity index to calculate the multidisciplinary diversity at the project level.

6.4. Modelling results and interpretations

6.4.1. Multiple membership and disciplinary diversity in projects

As stated above, GRAND requires Network Investigators, the primary researchers in projects, to be involved in at least two projects, and Collaborative Researchers to be involved in at least one. However, the opportunities of networking and collaborating with researchers in similar or diverse fields engaged with GRAND have encouraged many members to exceed the minimum requirement and be involved in several projects.

Because of this requirement, more NIs are involved in multiple projects than CRs. 44% of NIs are working on three projects. 24% of NIs are working on more than three projects. Three of them are even involved in five projects. We also found that 75% of CRs are working on only one project (Figure 3).

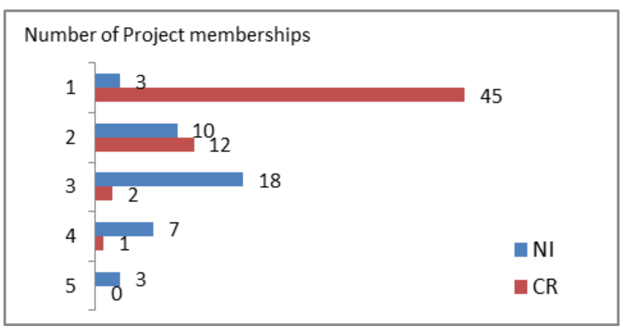

Fig. 3. Multiple membership in research projects in GRAND

Figure 4 illustrates the disciplinary diversity of each project. The squares represent each of the 32 projects, while the dots signify the 144 GRAND members. Various disciplines are sorted by colors. The average number of disciplines in each GRAND project is 3.34, but it may range from 1 to 6. The mean disciplinary diversity within projects is 0.51 with a standard deviation of 0.27.

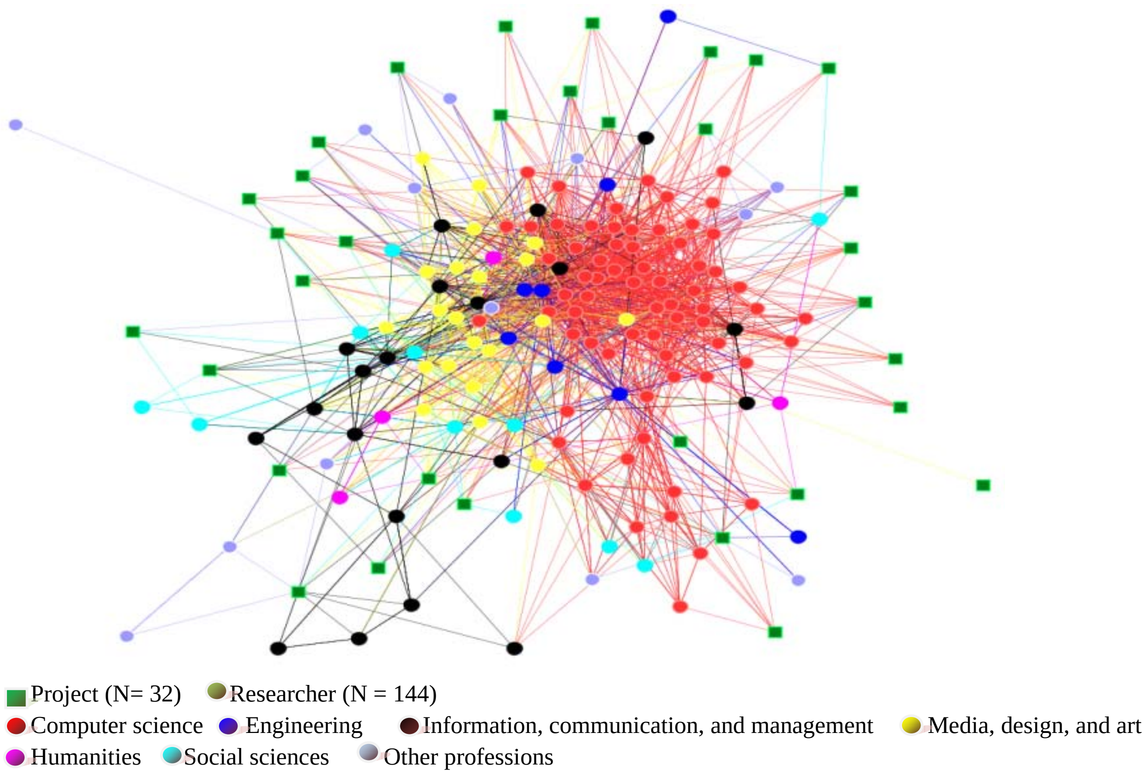

Fig. 4. Disciplinary diversity in GRAND projects

We found the mean diversity score in email networks to be 0.22 while that of the face-to-face network to be 0.39. The difference between the means indicates that the face-to-face network in which GRAND members are engaged are more multidisciplinary than their email networks.

6.4.2. Multiple membership multilevel model analysis

The first model (Table 1) is to specify and fit the multiple membership variance components to researchers' diversity scores in their communication networks at the individual level. The mean researcher is predicted to have a diversity score of 0.005 in their email network and 0.011 in their face-to-face network, with an intercept not significantly different from zero (z = 0.05 p = 0.96 in the email network and z = 0.09 p = 0.93 in the face-to-face network). This is expected as the response variable has been standardised to have both a mean of zero and a constant variance.

The between-project variance is estimated at 0.061 in the email network and 0.021 in the face-to-face network. The estimated patient level residual error variance is 0.945 in email network and 0.989 in face-to-face network.

These results show that, although individual level variables have stronger effects on the dependent variables, the multiple membership model is preferable to the single-level model because of a significant group level variance. In other words, the multiple membership model is a better fit for the analysis.

Having fit the model, we also predict empirical Bayesian estimates of the project effects together with their associated standard errors. We examine these predictions to check whether the random effects are normally distributed. The test reveals that the predicted project effects range from 0.301 to 0.223 with a difference of 0.524 between the highest and the lowest scoring project. This is large given that the dependent variable is standardized. A quantile-quantile plot shows that the project effects lie fairly close to the 45 degree line (Figure 5), suggesting that the predicted project effects are approximately normal.

Motivations for participating in multiple disciplinary collaborations (MDCs), compared with other individual level variables, have the strongest effect on diversity in both the email and the face-to-face networks. The coefficients on motivations to participate in MDCs (0.320, $p = 0.001$ in email network; 0.346, $p = 0.004$ in face-to-face network indicate that researchers who score one deviation higher in their motivations for working with collaborators from other disciplines, have 0.32 of one deviation greater diversity in their email network, and 0.346 of one deviation greater diversity in their face-to-face network.

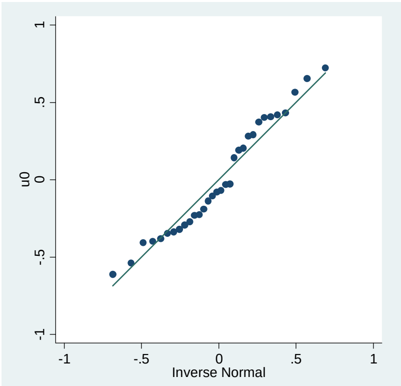

Fig. 5. Quantile-quantile plot for project effects in GRAND

	Model 1				Model 2				Model 3			
	Email		Face-to-face		Email		Face-to-face		Email		Face-to-face	
Intercept	0.005		0.011		-0.309		0.024		-0.855	***	-0.605	
Individual level variable												
Motivations					0.320	**	0.346	**	0.289	***	0.313	
Age					0.109		0.134		0.102		0.141	
Role in GRAND					0.278	**	0.248	*	0.293	**	0.26	
Academic ranking					0.007		0.049		0.029		0.055	
GIndex					0.149		0.141		0.191	*	0.173	
Gender					0.432	*	0.248		0.451	*	0.262	
% of researchers in same city					1.738		1.620		1.559		1.734	
Project-Level Variable												
Disciplinary Diversity									1.176	*	0.589	
Variance Estimates												
Group Variance	0.061	**	0.023	**	0.066	**	0.024	**	0.002	**	0.011	**
Individual Variance	0.945	**	0.989	**	0.594	**	0.675	**	0.567	**	0.66	**

Individual N=101, Project N=32

***p < .05; ** p<.01; *** p<.001**

Table 1. The role of a projects disciplinary diversity in explaining diversity in both the email and the face-to-face networks; multiple membership multilevel model.

Model 2 reveals that researchers in higher positions in GRAND are more likely to have greater diversity in their communication networks. Among all the indicators of status, a researchers' role in GRAND is the only one that is significantly associated with diversity in communication networks (β = 0.278 and p = 0.002 in the email network, while β = 0.248 and p = 0.011 in the face-to-face network).

Adding the individual level variables leads to an increase of 8.2% in the project level variance in the email network, and 4.3% in the face-to-face network. It also leads to a drop in the individual level variance of 40.1 in the email network, and 31.7% in the face-to-face network. The large decline in the individual level variance suggests that in both networks the project level effects of diversity on dependent variables are not as strong as the effects of individual level factors. This finding suggests that GRAND members are less constrained by the designed structure of multidisciplinary projects. Rather, their individual motivations and role are associated with their communication patterns.

Model 3 includes the project level variable of multidisciplinary diversity. It shows that multidisciplinary diversity in projects is positively related to diversity in the email network at the individual level. However, a good of fitness test shows that such relationship is not found in the face-to-face network. This finding suggests that face-to-face network may be less affected by the composition of disciplines in research projects. Model 3 shows that an increase of one standard deviation of multidisciplinary diversity within projects is associated with 1.176 standard deviation of diversity in the email network. This effect is about four times stronger than the effects of motivations to participate in MDCs on researchers' diversity score in the email network.

This model continues to confirm the effects of role in GRAND and motivations to participate in MDCs on diversity in the email network. Furthermore, a researcher's role shows a slightly stronger effect than their motivations for participating. If two collaborators are equally motivated to participate in MDCs, the one in a higher position is more likely to engage in a more multidisciplinary email network.

None of the cross-level interactions between disciplinary diversity and motivations to participate in MDCs, and disciplinary diversity and a researcher's role in GRAND are significant. This means that our hypotheses 4 and 5 are not supported.

7. Conclusions

In this paper, we proposed a specific data structure, both within-level and meso-level networks, in networked organizations. The data structure accommodates most of the organizational and network studies of multilevel networks where individuals are affiliated with more than one group. We propose the new multilevel multiple membership model to examine such structure.

Dissimilar from a hierarchical multilevel network structure, networked organizations are often characterized by flexible boundaries between groups, and individuals' affiliation with multiple groups. When individuals are members in more than one group simultaneously, their practices, performance, and interaction with other members in their individual networks are embedded in the groups they are affiliated with. In other words, individuals' behaviours are affected by the characteristics of the groups in which they are members. Our study views the affiliation network, consisting of individuals, groups, and ties connecting them, as the meso-level network. The purpose of using a multilevel multiple membership models is to include the meso-level structure into the framework of multilevel networks, as well as revealing how group characteristics shape individual networking behaviours through the meso-level network.

Our study of GRAND has shown that the joint characteristics of groups, compared to individual level factors, can have stronger effect on an individual's networking behaviour. Comparing two individual level networks, we also indicated that the joint characteristics of groups affect networks in various domains differently, such as in their email and face-to-face communication networks. By comparing the models with and without the interaction effects, our example revealed that cross-level effects, though treated more as an inherent structure in the form of affiliation networks, provide better fits to the data and simplified the complexity of the meso-level dada.

Although developed for a particular type of network data, multilevel multiple membership models are also applicable for multilevel network data from non-organizational settings because they do not require ties among group level nodes. In organizations, nodes at the group level are defined by the intrinsic formal division, such as teams, groups, and departments. However, in non-organizational settings, we can create group-level nodes from common attributes of individual nodes. For example, if individual nodes are people, their attribute data are countries they used to live, we can define countries as group-level nodes. In this case, a person who has lived in three countries would be classified as being affiliated with three groups. In this way, we can construct multilevel multiple membership data by transforming the attribute data into nodes at the group level.

Regardless of the important role that the meso-level network plays in multilevel multiple membership networks, it is treated as a fixed and internal component of the group itself. As a result, rather than elaborating on the effects that multiple memberships have on the individual level network, our models provide more insights into the mechanisms of multilevel networks within networked organizations. For example, we are able to show how a groups attributes, or its network features jointly affect an individual's position in their networks, as well as their networking behaviours, and structural features of their ego networks.

Furthermore, our proposed models can be used to evaluate the effects of organizational design. As Bate et al. (2000) have pointed out, the goal of organizational design is shifting from one of "division" to one of " networked community" because networks allow "an alteration of organizational norms, interactions and power arrangements". Social network analysis provides promising insights and methods to assess organizations' strategies for network design (Kilduff and Tsai, 2003; Reagans et al., 2004; Sinha and Ven, 2005). When the notion of networked organizations is becoming more and more accepted in organizational design, the multilevel multiple member models presented in this article may enable researchers to evaluate the effects of such designs and the performance of individuals and groups within them.

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